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Analysis and Implementation of the Artificial Neural Network (ANN) Approach for the Integration of Solar and Wind Energy Sources into Telecommunication Systems

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ABSTRACT
In order to sustain monetary growth, the introduction of renewable energy into the electricity grid is crucial especially for many foreign African locations. Thus, in order to reap sustainable strength, these foreign locations may also outfit their airport electrical equipment with advanced synthetic intelligence technologies. For a distributive hybrid solar strength grid, the paper attempts to propose an actual-time energy management algorithm. It continues with the combining of photovoltaic and wind energy for network simulation. As a function of the number of wind aero-mills and photovoltaic solar panels, a multi-goal approach is proposed to optimize the spectral efficiency of the location and the energy performance. For the MATLAB software simulation, radio criteria for Cell Wireless Interoperability Medium Access (WiMAX) technologies are taken into account. The obtained effects are much mitigated however theoretically encouraging for the mixing of green energy integration into the modern telecommunication structures.

KEYWORDS: *Artificial neural network (ANN), Green energy, multi-objective problem, Power generation optimization, Theoretical formulation, Solar & Wind radiation prediction.*

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1. INTRODUCTION
Mobile cellular networks run on a small spectrum and time slot [1], [2] at a speed of increasing consumer growth, which translates into high power consumption but also emits CO2. It was noted in [3] that the Information Communication and Technology (ICT) industries absorbed around 3% of global energy and accounted for about 2% of global CO2 emissions. In this respect, the ICT industries are faced with a growth of 16-20 per cent per year in related energy usage. Power consumption ratio has demonstrated that the power consumption for the Main Network (RAN) is approximately 30 per cent, the Base Band Processing Unit is approximately 10-15 per cent and the Cooling System is approximately 15 percent. The number of base stations in 2015 has been projected at about 6 million worldwide, which is projected to increase by 2020[4]. It is imperative that the energy consumption reduction of the new wireless infrastructure is also important for the future [4], because not only is global warming a real problem. In [5], a low electrification rate was emphasized in the regions of Central Africa, estimated at around 13 per cent, and the reference [6] suggested that sub-Saharan electrification was estimated at 13 per cent. Africa has an electrification rate of 7% in its rural areas. Industrialized countries, such as Finland, France and Germany, have developed a road map for electricity with universal access for all at a rate of 100% penetration by 2030 with the introduction of renewable energy into domestic consumption [7]. A variety of forums have concentrated on hybrid power generation from green energy sources in

order to increase the cost of electricity for universal access. In fact, the International Energy Agency (IEA) [8] has calculated that the rate of solar energy will be the same. Approximately 11 per cent of the overall energy produced by the year 2050. In addition, the Global Energy Vision 2100, headed by the German Advisory Council on Global Change, suggested that solar energy generation would contribute almost 20 per cent in 2050 and 60 per cent in 2100 to global energy production [9]. Subsequently, on the grounds that all mobile providers must use renewable energy to supply telecommunications on the continent, a substantial amount of green energy will be pumped into many African nation's power grids on a daily basis. When referring to the statistics provided in 2015 by the Togolese Authority of Regulation of Telecommunication and Post services (ARTP), these reports indicated a number of 858 GSM sites and 1080 BTS for 3Generation. Assuming, a 1000 GSM sites with an average power consumption of 4 kW per site that will approximate a demand of 40 00kW or 4 MW. In 2015, at Kumasi airport, the entire electrical system failed to respond, including all the tarmac (runway) lighting system, when a commercial plane was about to land. The diesel generator also failed to start. The blackout lasted about 5 to 6mn. Such a problem may result in voltage drop and the power quality, thus power stability management. The paper seeks to propose a real time power management system for a distributive hybrid renewable energy grid, while considering a telecommunication system located in some critical areas such as an airport. The contribution of this paper resides in the proposition of the power management on a distributive hybrid grid using an artificial neural network (ANN). The relaxation of the paper is hooked up as follows, section 2 formulates the mathematical derivation of the power overall performance as a feature of the massive form of wind aero generators and the photovoltaic panels. Section three explains the synoptic block diagram of the implanted manipulate tool primarily based mostly on the artificial neural network and the simulation parameters. The subsequent phase makes a robust element of the presentation of the consequences and the evaluation. The remaining section (5) closes the paper with a succinct end.

1.1 ARTIFICIAL NEURAL NETWORKS

The concept of neural network analysis was discovered nearly 50 years ago, but it is only in the last 20 years that applications software has been developed to handle practical problems. The history and theory of neural networks have been described in a large number of published literatures and will not be covered in this paper except for a very brief overview of how neural networks operate. ANNs have been applied successfully in various fields of mathematics, engineering, medicine, economics, meteorology, psychology, neurology, and many others. Some of the most important ones are; in pattern, sound and speech recognition, in the analysis of electromyography and other medical signatures, in the identification of military targets and in the identification of explosives in passenger suitcases. They have also been used in weather and market trends forecasting, in the prediction of mineral exploration sites, in electrical and thermal load prediction, in adaptive and robotic control and many others. Neural networks are used for process control because they can build predictive models of the process from multidimensional data routinely collected from sensors. Artificial neural network models may be used as an alternative method in engineering analysis and predictions. ANN mimic somewhat the learning process of a human brain. They operate like a 'black box' model, requiring no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data. ANN can also be compared to multiple regression analysis except that with ANN no assumptions need to be made about the system to be modelled. Neural networks usually perform successfully where other methods do not, and have been applied in solving a wide variety of problems, including non-linear problems such as pattern recognition, that are not well suited to classical methods of analysis. Another advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters. They seem to simply ignore excess data that are of minimal significance and concentrate instead on the more important inputs. Instead of complex rules and mathematical routines, artificial neural networks are able to learn the key information patterns within a multidimensional information domain. In addition, neural networks are fault tolerant, robust, and noise immune [1]. The best example of a neural network is probably the human brain. In fact, the human brain is the most complex and powerful structure known today. Artificial neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. A schematic diagram of typical multilayer feed-forward neural network architecture is shown in Fig. 1. Although two hidden layers are shown, their number can be one or more than two, depending on

the problem examined. In its simple form, each single neuron is connected to all other neurons of a previous layer through adaptable synaptic weights. The number of input and output parameters and the number of cases influence the geometry of the network. The network consists of an 'input' layer of neurons, with one neuron corresponding to each input parameter, a 'hidden' layer or layers of neurons and an output layer of one neuron for each output. A neuron, also called processing element, is the basic unit of a neural network and performs summation and activation functions to determine the output of that neuron. The number of neurons in the hidden layer is approximately the average of the inputs and outputs though it does depend also on the number of training cases. Too many hidden layer neurons can result in 'over-training' (or lack of generalization) and lead to large 'verification' errors. Too few neurons can result in large 'training' and 'verification' errors. Knowledge is usually stored as a set of connection weights (presumably corresponding to synapse efficacy in biological neural systems). A training set is a group of matched input and output patterns used for training the network, usually by suitable adaptation of the synaptic weights. The outputs are the dependent variables that the network produces for the corresponding input. It is important that all the information the network needs to learn is supplied to the network as a data set. Starting from an initially randomised weighted network system, input data is propagated through the network to provide an estimate of the output value. When each pattern is read, the network uses the input data to produce an output, which is then compared to the training pattern, i.e., the correct or desired output. If there is a difference, the connection weights (usually but not always) are altered in such a direction that the error is decreased. After the network has run through all the input patterns, if the error is still greater than the maximum desired tolerance, the ANN runs again through all the input patterns repeatedly until all the errors are within the required tolerance. When the training reaches a satisfactory level, the network holds the weights constant and uses the trained network to make decisions, identify patterns, or define associations in new input data sets not used to train it.

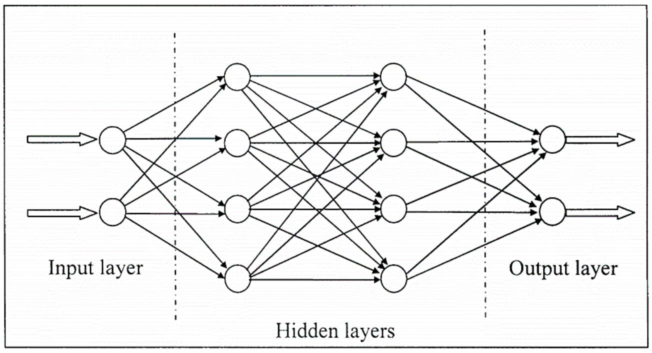

Figure 1. Schematic diagram of a fully connected multilayer feed-forward neural network.

2. MODELING

The system consists of one macro-cell, pico-cells, three relays, and femto-cells.

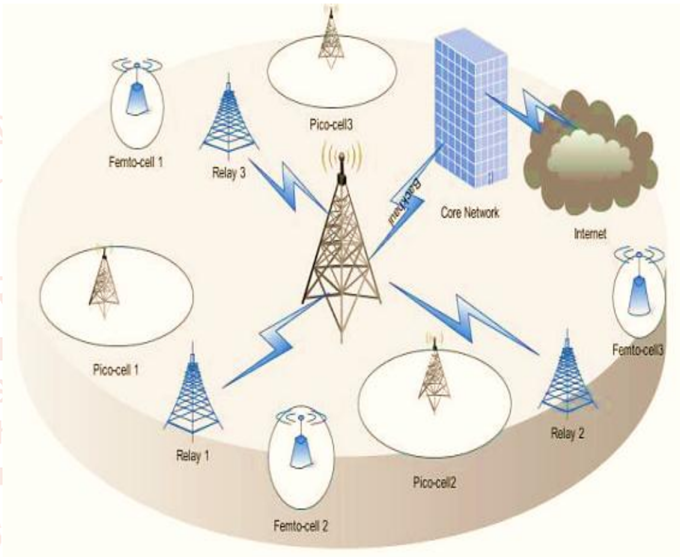

Fig. 2: the descriptive system of the study

The transmitters K are empowered by a micro-grid and the renewable energy sources are used to reduce the emission of the dioxide of carbon. It is assumed that each transmitter serves N users.

The power consumption of an active node, $\boldsymbol{P_K}$ for the downlink service can be expressed as:

$$P_{i,k} = P_{Ti,k} + P_o - P_g \quad (1)$$

$\boldsymbol{P_{T\,i,k}}$ is the downlink transmission dependent, $\boldsymbol{P_o}$ is the uplink transmission dependent that includes the data processing, the non-transmission, cooling, lighting, etc… and, $\boldsymbol{P_g}$,the green injected power, into the system, that aims at reducing the dioxide of carbon emission. The transmitted power for the downlink service, $\boldsymbol{P_{T\,i,k}}$ to a user attached to the cell k, is formulated as:

$$P_{T\,i,k} = P_{i,k} - P_o - P_g \quad (2)$$

$\boldsymbol{P_{gr}}$ the injected green power in the system to the total required power of the system, $\boldsymbol{P_{TO}}$, comes as:

$$\boldsymbol{P_{TO} + S_o(k_o.C_{cst}) + (1 - s_o)([(1 - k_o)(m.P_{PV} + n.G_V)])} \quad (3)$$

The total injected green power $\boldsymbol{P_{gr}}$ is calculated as: $\boldsymbol{P_{gr} = m.P_{pv} + N.P_w}$ (4)

With, the number of solar panels; and $\boldsymbol{n}$, the number of wind generators

For the photovoltaic power, $\boldsymbol{P_{PV}}$, is computed as;

$$\boldsymbol{P_{PV} = \eta_{ref} \times A \times G_{ref}} \quad (5)$$

The energy produced by the solar panel is given as

$$\boldsymbol{E_{PV} = P_{PV} * I_T * k} \quad (6)$$

where the indice of the clarity $\boldsymbol{k = [0.3 : 0.85]}$, $\boldsymbol{PV}$, Power peak of the panel in kWc, $\boldsymbol{I_T}$,total irradiation on the panel surface kWh/m²/day.

For the wind power, $\boldsymbol{P_W}$, is specified as:

$$\boldsymbol{P_W = \frac{1}{2} C_p.\rho.A.V^3} \quad (7)$$

Where

$\boldsymbol{C_p}$ **:** 22/7, $\boldsymbol{\rho}$ density $\boldsymbol{A}$, is the cross-sectional area, $\boldsymbol{V}$, the wind speed;

$$\boldsymbol{\eta_{SEk}(i) = log_2(1 + \gamma_{i,k_{pi}})} \quad (8)$$

The total spectral efficiency $\boldsymbol{\eta_{Ai,k}}$, is expressed as:

$$\boldsymbol{\eta_{Ai,k,Dl} = \sum_{k=1}^{K}\sum_{i=1}^{N}\eta_{SE_{i,k}}(i)} \quad (9)$$

A scheduling monotonic rate is assumed:

$$\boldsymbol{\eta_{Ai,k_{Dl}} = \frac{\sum_{k=1}^{K}\sum_{i=1}^{N}\eta_{SE_{i,k}}(i)}{T_{max}}} \quad (10)$$

Where the $\boldsymbol{T_{max}}$ is the total transmission time to serve all users.

The green telecommunications' metric, $\boldsymbol{\rho_{green}}$, is defined as:

$$\boldsymbol{\rho_g = \frac{\sum_i^k \eta_{A_{i,k}}}{\sum_i^K F_{i,k}\, P_{i,k}}} \quad (11)$$

$\boldsymbol{F_{i,k}}$ is the associated rate of dioxide of carbon emission of the energy source.

The total cost of the energy is given as:

$$\boldsymbol{TC = \sum_{t}^{N} C_{C_t} * C_{a_t} + f_{oc_t} * C_{a_t} + V_{c_t} * P_t + C_e * T_{GHG}} \quad (12)$$

Cc : the investment capital of the technology

Ca : the size of the installed power

Vc : the cost of maintenance and operational parameters involved,

Foc : the fixed cost ;

Ce : the external cost due to the CO_2 emission,

$\mathbf{T_{GHG}}$: the total rate of the CO_2 emission associated to the power generation

In multi-transmitter system, the total transmitted power is given as:

$$\boldsymbol{\sum_{k=1}^{K}\sum_{i=1}^{M} P_{Ti,k} = P_{TO} - P_g - \sum_{1}^{K} P_{o,k}} \quad (13)$$

$\boldsymbol{P_{o,k}}$ the power of other low consumption nodes which is neglected for the simplification purpose, and $\boldsymbol{P_{TO} = \sum P_{i,k}}$ The energy efficiency of the system is calculated by

$$\boldsymbol{\gamma_{ss_{Dl}} = \frac{\rho_g.\sum_i^K F_{i,k}\, P_{i,k}}{S_o(k_o.C_{cst})(1 - S_o)([(1 - k_o)(m.P_{PV} + n.G_W)] - N_s}} \quad (14)$$

$\boldsymbol{F_{i,k}}$ is the factor of emission of the power technology used,

$\boldsymbol{P_{i,k}}$, the power consumption at a node.

$\boldsymbol{m}$: the number of solar panels

$\boldsymbol{n}$: the number of wind generators

$\boldsymbol{N_B}$: the number of battery

The optimization problem consists to maximize the spectral efficiency (SE), $\boldsymbol{\eta_{A_{i,k}}}$ and the energy efficiency (EE), $\boldsymbol{\gamma_{EE_{Dl}}}$, for the cell, $\boldsymbol{k}$, which is given as:

$$\boldsymbol{Max\,(\eta_{EE_{Dl}}, \eta_{A_{i,k}})} \quad (15)$$

Subject to

$$\boldsymbol{\sum_{i=1}^{N} P_{i,k} \leq P_{TO}^{max}} \quad (16)$$

$$\boldsymbol{1 \leq m \leq max} \quad (17)$$

$$\boldsymbol{1 \leq n \leq max} \quad (18)$$

$$\boldsymbol{1 \leq N_B \leq max} \quad (19)$$

The number of solar panel (m) and aero-generators (n) needed could be obtained by the minimization of the Root Mean Square error function as

$$\varepsilon(\boldsymbol{c, m, n}) = \left(\frac{\mathbf{1}}{\boldsymbol{l}}\right)\sum_{i=1}^{l}[\gamma_i - \boldsymbol{P_{TO \to i}}]^2 \quad (20)$$

Where $\boldsymbol{\gamma_i}$ is the measured value, $\boldsymbol{l}$ is the volume of the measurement sample set, and $\boldsymbol{P_{TO \to i}}$ the theoretical power generated. Which implies that, all

the partial derivatives of the $\boldsymbol{err}\ (\boldsymbol{c}, \boldsymbol{m}, \boldsymbol{n})$ function must equal to zero.

$$\Rightarrow \begin{cases} \frac{\partial err}{\partial c} = 0 \\ \frac{\partial err}{\partial m} = 0 \\ \frac{\partial err}{\partial n} = 0 \end{cases} \qquad (21)$$

This can be written in square matrix as:

$$W \times \bar{y} \coloneqq \begin{bmatrix} C_1 & 1 \\ C_2 & 1 \\ C_m & 1 \end{bmatrix} \times \begin{bmatrix} m \\ n \end{bmatrix} \qquad (22)$$

The optimal correction coefficients C, m and n fulfilling the least square conditions are obtained from the least-squares solutions that are given as:

$$\bar{C}_{LS} = [W^T W]^{-1} W^T Y \qquad (23)$$

3. Methodology

A. Radio parameters and block diagram: Table 1 shows the radio system settings for the simulation. The cascaded artificial neural networks illustrated in Fig. 3 were used in the system modeling. The usage of an artificial neural network attempts to forecast worldwide sun irradiation and wind speed in advance. The data was gathered by downloading the NASA database's daily irradiation and wind speed records. Some of these data were utilized in the training stage of the first artificial neural network, which collects worldwide sun irradiation for photovoltaic energy optimization. The second artificial neural network forecasts wind speed in order to maximize wind energy output. The third artificial neural network selects the best available energy source, including the energy storage device on the micro-distributive grid's bus. Table 1 shows the system parameters for the simulation. A random noise is used to simulate the route loss for a connection between a macro cell and user equipment, as well as the user transmission power. A regression method may be used to calculate the necessary number of solar panels and aero-generators (Wind turbines) for the proposed mobile WiMAX system, as well as the overall power budget of the facility. This is not included in the current work. With knowledge of the typical wind speed at the Lome-site, which is about 4m/s. This indicates that a modest wind turbine would be an acceptable choice.

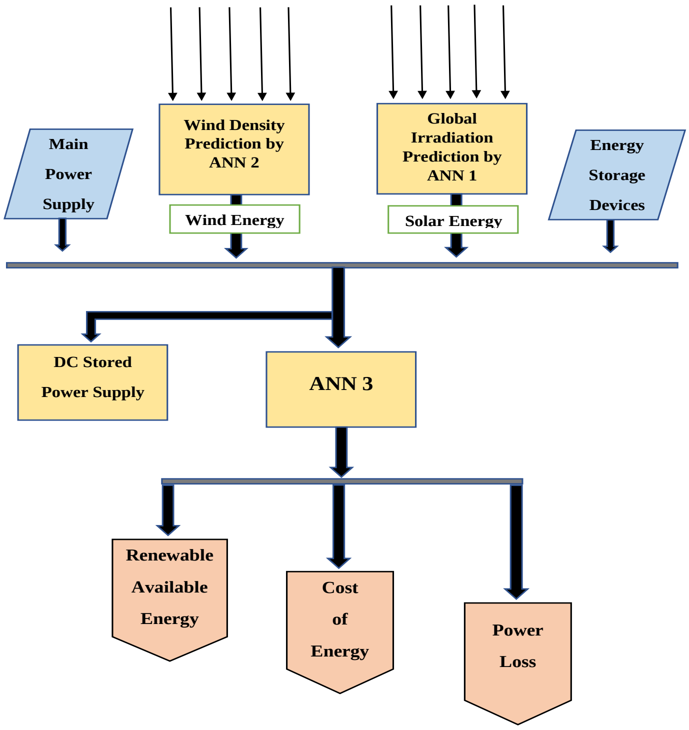

Fig. 3: The cascaded ANN system

Table 1: Simulation Parameters

Description	Symbol	Mobile WiMAX
Number of Users	N	150 1500
Constant related to the cell-size distribution	a	0.6
User Density	$\mu = u$	0.95
BS Density	λ_b	0.15
Femto-cell Density	λ_f	0.55
Pico-cell Density	λ_p	0.25
BS-User density	$d = b/u$	
Variance of AWGN channel	D	25
Environment fading	h	1
Operating frequency	f	20 Ghz
The circuit power of transceivers	P_c	100
The non-transmission power consumption	P_o	
Digital signal processor	P_{dxy}	100
Signal generator	P_{gen}	384
AC-DC converter	P_{conv}	100
Backhaul link equipment	P_{link}	80
Air-conditioner	P_{cool}	690

4. RESULTS & DISCUSSION

This chapter presents the results and their respective analysis. The predicted responses of the various ANNs are illustrated. The Fig. 4.1 provide the output of the global solar irradiation for a selected area. It will be added that the optimal production of the solar photovoltaic energy will definitely require accurate data and an assisted supervision system.

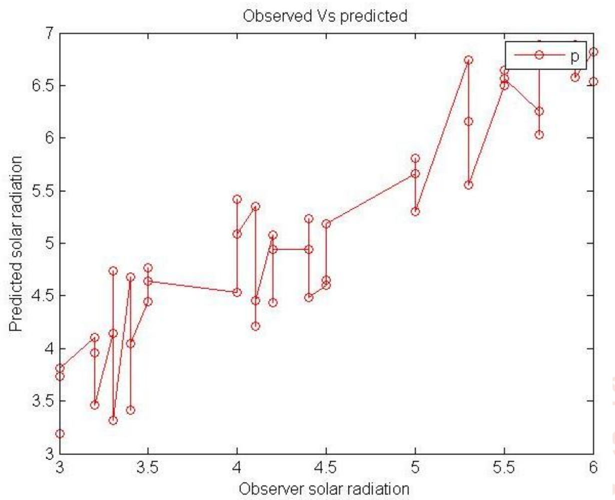

Fig: 4.1Predicted global solar irradiation using ANN1

The output of the second neural network is showing that the global solar irradiation is in the range of 4.5 to 6kWh/m2/jr. The Fig. 4.2 may indicate that for the wind speed below 2m/s, the ANN2-multiaayer perceptron layer configuration may give a high prediction, however for wind speed above 6m/s the predicted value may be lower than the observed value on the site. For wind speed in between 2m/s and 6m/s, the graph may point out that a strong agreement with the predicted data against the observed data is achieved.

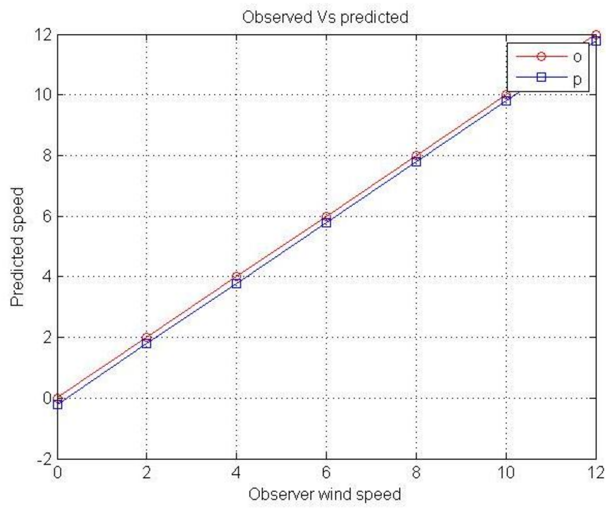

Fig 4.2: Predicted wind speed using ANN2

The artificial neural network 3 provides information about the system energy efficiency and spectral efficiency of a fixed-mobile WiMAX station with the single input and single output (SISO) antenna configuration. It is assumed to serve a delicate area; in this study an airport was considered. Three data services were considered, the system energy efficiency against the signal to noise ratio and the nodes respectively in the Fig. 4.3. The analysis (energy efficiency against the snr) is indicating that the energy efficiency is improved as the number of nodes increases. It reaches a maximum point but a compromise should be made, whatever the kind of data services. However, increasing the transmitting power of the macro-cell BS will not necessarily improve the area spectral efficiency, but when using more small cells deployment this could be achieved. In addition, the small cells (femto, pico – cells) are very low power consumption devices, energy harvesting in the environment could be therefore very beneficial but their number under a given macro-cell should be chosen with caution. All the results that we have obtained are shown in fig 4.1 to Fig 4.4, It indicates the injected green energy as function of the number of the small cells. The optimal Value of the spectral efficiency is subject to the number of small cells under the macro-cell base station.

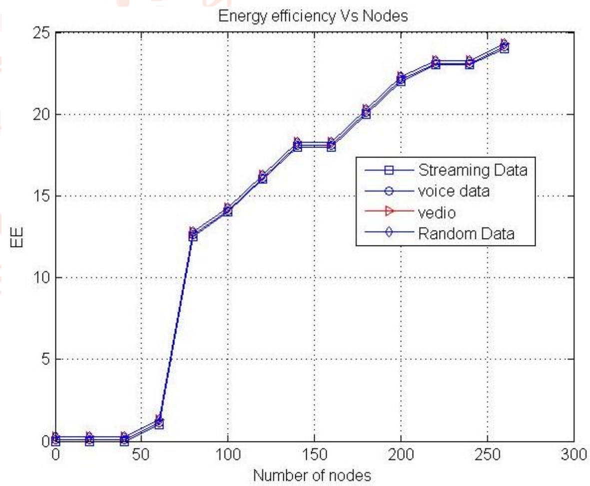

Fig4.3: Comparison between energy and nodes

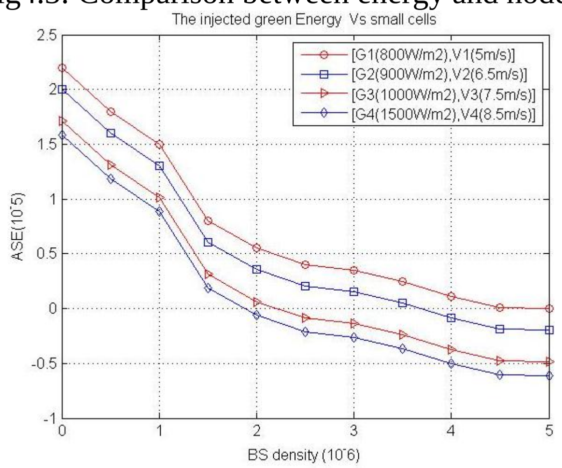

Fig 4.4 ASE vs. Density

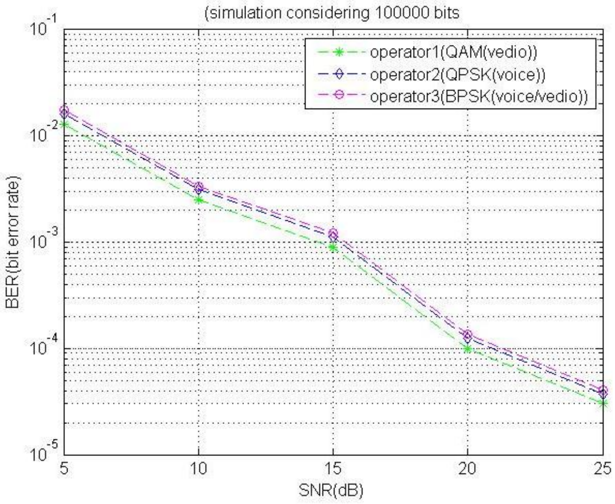

Fig. 4.5 shows the comparison between bit error rate and Signal to noise Ratio (SNR)

Figure 4.5 shows the comparison between bit error rate and Signal to noise Ratio (SNR) for different type of data considering various modulation methods. SNR is being increased from 5db to 25 db .At each value of SNR a specific value of BER is measured and shown. As the SNR is increasing noise power is reducing and therefore less number of bits are lost .Similarly when the SNR is minimum it means noise power is maximum and more number of data bits gets lost. Figure also shows the performance comparison of different modulation schemes from different operator, as it can be seen from the figure that operator 2 and 3 gives the best results in terms of BER. We have taken operators on the basis of type of data they transmit (voice, vedio, etc.)

Energy efficiency VS Nodes Old Data.

S N o.	Number of nodes	Energy Efficiency **Streaming data**	Energy Efficiency **Voice data**	Energy Efficiency **Video**	Energy Efficiency **Random data**
1.	0	0	0	0	0
2.	20	0	0	0	0
3.	40	0	0	0	0
4.	60	1	1.2	1.3	1
5.	80	12.3	12.4	12.4	12.3
6.	100	13.5	13.3	13.4	13.5
7.	120	13.8	13.9	13.7	13.8
8.	140	14.5	14.4	14.3	14.6
9.	160	15.5	15.6	15.7	15.9

Energy efficiency VS Nodes New Data.

S N o.	Number of nodes	Energy Efficiency **Streaming data**	Energy Efficiency **Voice data**	Energy Efficiency **Video**	Energy Efficiency **Random data**
1.	0	0	0	0	0
2.	60	1.3	1.5	1.4	1.6
3.	80	13.0	13.2	13.1	13.4
4.	100	14.4	14.5	14.6	14.5
5.	125	16.2	16.3	16.2	16.4
6.	140	17.5	17.6	17.5	17.7
7.	160	17.4	17.5	17.4	17.6
8.	180	20.0	20.1	20.0	20.1
9.	200	22.5	22.6	22.5	22.4
10	220	23.2	23.3	23.2	23.4

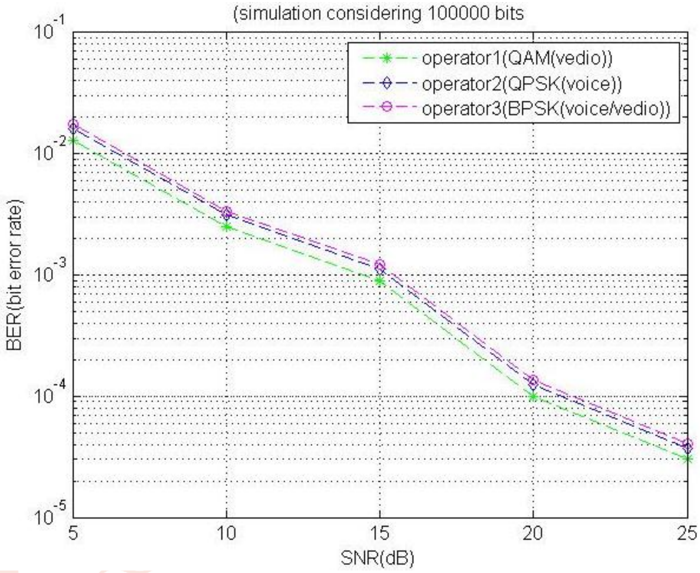

Fig 6: BER (bit error rate) and SNR (dB)

Figure 6 shows the comparison between bit error rate and Signal to noise Ratio (SNR) for different type of data considering various modulation methods. SNR is being increased from 5 db to 25 db. At each value of SNR a specific value of BER is measured and shown. As the SNR is increasing noise power is reducing and therefore a smaller number of bits are lost. Similarly, when the SNR is minimum it means noise power is maximum and a greater number of data bits gets lost. Figure also shows the performance comparison of different modulation schemes from different operator, as it can be seen from the figure that operator 2 and 3 gives the best results in terms of BER. We have taken operators on the basis of type of data they transmit (voice, video, etc.)

5. CONCLUSION & FUTURE SCOPE

The integration of the renewable energy into the power grid is very important nowadays, particularly

for African nations that possess a huge reserve of natural energy resources. Blessing is the sun for African, and many of the coastal country could also equip the airport's electrical system with advanced artificial intelligence technology. This paper explores and formulates the integration of green energy into telecommunication system with power management based on artificial neural network. The contribution of this paper resides in proposing a power management of a distributive hybrid grid using an (ANN). The study demonstrates the importance of the heterogeneous network, and further shows increasing the macro-cell BS transmitting will not improve the system spectral efficiency. The green metric is derived as function of the injected green energy, and the availability of the green energy. Many method could be used to solve the multi-objective problem. The Pareto method could also be used as well as the dual Lagrange. Further validation of this problem will be carried out using on site data and the dynamic monitoring of the number of solar panels and the wind aero-generators will ideally be important. Such information could be made available if advanced artificial intelligence system is put in place. In the future research, the algorithm of the power management will be considered based on the power system quality and stability in a real time monitoring. The system voltage drop and power loss will also be investigated.

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